ECONOMIES OF SCOPE OF LENDING AND MOBILIZING DEPOSITS IN RURAL MICROFINANCE INSTITUTIONS: A SEMIPARAMETRIC ANALYSIS

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Microfinance emerged as an innovation in lending to the rural poor in Asia and in response to frequent failure of previous interventions in rural financial markets such as directed and subsidized production credit disbursed by agricultural development banks. While it started "as a collection of banking practices built around providing small loans (typically without collateral) and accepting tiny savings deposits" Armendariz de Aghion and Morduch (2005, p. 1), today many microfinance institutions (MFIs) expand their services and strive to offer payment and savings facilities, insurance, housing, and longer-term loans to marginalized clientele in rural and urban settings.

Estimates show that there are at least 10,000 microfinance programs worldwide. Two related and important trends are now emerging. The first is toward commercialization which essentially is transforming NGO-MFIs into regulated intermediaries with the intent to lower costs by accessing deposits as well as strengthen the organizations by privatization. The second trend is a renewed interest in experimentation to mobilize savings with emphasis on rural savings. Economies of scope imply that expansion into the savings market can be more cost efficient if done by the same MFIs, which makes it a significant factor in assessing the feasibility of these innovations. However, there are few studies that estimate the magnitude and sign of scope economies. In this paper, we present some preliminary evidence on scope economies using a large sample of MFIs.

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Aside from Hartarska, Parmeter and Mersland (2009), we are the first to estimate scope economies in microfinance. Whereas Hartarska, Parmeter and Mersland (2009) focused on pure estimation of scope economies and their magnitude across a variety of factors/regions, we investigate a much more comprehensive list of MFIs in addition to focusing on the distinction between fixed-cost economies and cost-complementarities. This is important since these components can provide further insight into the nature and magnitude of scope economies. In addition, we provide a novel approach to dealing with extreme observations in applied non/semiparametric settings. This approach has merit regardless of context across economic subdisciplines.

Our findings indicate that policies designed to improve MFIs' performance to expand their services should be based on regional, organizational, and characteristics of the environment in which MFIs operate. The analysis suggests that economies of scope are driven mostly by fixed cost sharing while we do not find cost complementarities in most regions and MFI types.

The plan of the paper is as follows. We first discuss the theoretical and econometric techniques needed to estimate scope economies. We then proceed to detail the MFI data which we use in this study. Next, the results from our econometric investigation are present while conclusions and direction for future research finish our paper.

Estimation of economies of scope

Pulley and Humphrey (1993) define overall economies of scope as the percentage of cost savings from producing all outputs jointly as opposed to producing each output separately. Here we have only two outputs (q_1, and q_2), loans and deposits, so our estimates of scope economies are:

$$SCOPE = \frac{C(q_1, 0; \bar{r}) + C(0, q_2; \bar{r}) - C(q_1, q_2; \bar{r})}{C(q_1, q_2; \bar{r})}, \tag{1}$$

where $\bar{r}$ is a vector of ℓ input prices (here taken to be the relative price of labor and borrowed funds), and $C(\cdot)$ is the cost function. Given that the data used to estimate the cost function will represent a mix of firms producing loans and deposits jointly and firms specializing in the production of loans exclusively, the use of standard cost functions in production econometrics are not suitable. For example, the transcendental logarithmic cost function (Christiansen, Jorgensen and Lau 1971) cannot directly handle zero outputs. Thus, the use of a logarithmic style cost function for the study of economies of scope is in general restrictive and inappropriate for a wide array of empirical problems.[1]

An empirical cost function for estimating scope economies was suggested by Pulley and Braunstein (1992, PB hereafter) based on of the theoretical cost function suggested by Baumol, Panzer and Willig (1982). Their cost function is multiplicatively separable in outputs and input prices and is quadratic (as opposed to log-quadratic) in outputs, thus alleviating the empirical issue of zero valued outputs in real world data sets. The composite cost model of PB can be written more succinctly as

$$C(q, \ln r) = F(q, \ln r) \cdot \tilde{G}(\ln r) + u. \tag{2}$$

Semiparametric Smooth Coefficient Cost Function

The empirical model of PB reflects a composite structure suitable for estimating scope economies, Asaftei, Parmeter and Yuan (2009) recently proposed a semiparametric smooth coefficient cost function (SPSCC) that takes a similarly representative form but relaxes the specific functional form restrictions on $\tilde{G}(\ln r)$.[2] This setup, with the same type of cost structure for $F(q, \ln r)$, affords the researcher sufficient flexibility to model costs and investigate scope economies. While the theoretical properties of cost functions are well known with traditional input prices, the use of environmental variable is less well understood. Thus, the ability to introduce these variables in a manner that imposes little structure on their exact specification within the cost function is pertinent. Additionally, given the importance of environmental factors on microfinance institutions (Armedariz and Szafarz 2009), our ability to control these influences in a general way is desirable.

We can write equation (2) in the following SPSCM specification,

$$y_i = \alpha(z_i) + \beta(z_i)x_i + \varepsilon_i \tag{3}$$

where $y_i \equiv C_i$, $x_i = [1 \quad q_i' \quad qq_i' \quad q\ln r_i']'$, $z_i = [\ln r_i \quad V_i]$ and where q_i represents the vector of outputs for the i^{th} firm, r_i is the vector of input prices and V_i encapsulate our environmental variables. Here, qq_i' is the $k(k-1) \times 1$ vector of squares and interactions of the outputs and $q\ln r_i'$ is the $kj \times 1$ vector of interactions between outputs and log input prices.

Another way to think of this model is that for a given level of z_i, we have a linear-in-parameters model where the slopes possibly differ for differing levels of z_i. SOne can view the original PB model as a smooth coefficient model.The key difference between the semi-parametric smooth coefficient model in equation (3) and the parametric smooth coefficient model of PB is that the coefficients are identical, up to scale, in the parametric model proposed by PB while in equation (3) they can be entirely different functions altogether.

Li et al. (2002) and Li and Racine (2009) proposed an estimation procedure for the SPSCM defined in equation (3) based on local constant least squares (LCLS). The estimation of equation (3) is as follows. Denote $\delta(z_i) = [\alpha(z_i), \beta(z_i)]$ and rewrite (3) as $y_i = \delta(z_i)X_i + \varepsilon_i$, where $X_i = [1 \ x_i]$. Our LCLS estimator of $\delta(z)$ becomes

$$\delta(z) = (\mathbf{X}'\mathbf{K}(z)\mathbf{X})^{-1}\mathbf{X}'\mathbf{K}(z)\mathbf{y}, \tag{4}$$

where $\mathbf{K}(z)$ is a diagonal matrix with i^{th} element $K_i = K_\gamma(z_i, z)$ and $\mathbf{X}$ is our matrix composed of X_i. K_i is constructed using the generalized product kernel of Racine and Li (2004) and γ is a vector of bandwidths.[3] The reason we use a generalized kernel is that several of our environmental variables are discrete,[4] most notably our indicator for loan method and area serviced by the MFI. Smoothing these types of variables with continuous kernels is inappropriate while treating it as a dummy variable leads to a loss of efficiency in our estimates of the smooth coefficients.

Fixed and Complementary Costs

Once we have estimated our SPSC cost function we can easily obtain scope economies from (1) as

$$SCOPE = \frac{\alpha(z) - \beta_{1,2}(z)q_1q_2}{TC}, \tag{5}$$

where $\beta_{1,2}(z)$ is the coefficient on the interaction between the two outputs produced by MFIs and TC represents estimated total costs. We can decompose $\alpha(z)$ into two separate components to obtain the contribution of fixed costs to our scope economies. That is, since input prices are a component of z, we have to evaluate $\alpha(z)$ at 0 input prices, holding the remaining environmental variables fixed to obtain a 'true' intercept representing fixed costs. Thus, we can break up our intercept as

$$\alpha(z) = \alpha(0, z_-) + (\alpha(z) - \alpha(0, z_-)). \tag{6}$$

Here the notation z_- is taken to mean our original z vector excluding input prices, which have been set to zero.

Using this division of our intercept we can decompose scope economies into fixed and complementary cost components. We have

$$\begin{aligned} SCOPE =& \frac{\alpha(0, z_-) + (\alpha(z) - \alpha(0, z_-)) - \beta_{1,2}(z)q_1q_2}{TC} \\ =& \frac{\alpha(0, z_-)}{TC} + \frac{(\alpha(z) - \alpha(0, z_-)) - \beta_{1,2}(z)q_1q_2}{TC} \\ =& SCOPE_{FC} + SCOPE_{CC}. \end{aligned} \tag{7}$$

Scope economies arise through fixed costs by spreading costs over an expanded set of outputs whereas scope economies arise through cost complementarities if variable inputs are shared across alternative outputs. Specifically, cost complementarities accrue to MFIs if the account information that is developed in the process of creating deposits is subsequently used to help monitor and gather credit information on loans for the same customer base. Spreading fixed costs over an enhanced product base produces scope economies if the same set of tools required to manage deposits can also be used to produce and monitor loans.

Data

The data were collected from the MIXMARKET database on November 1st 2008. At that time, the database consisted of over 1,300 MFIs. Most MFIs had data for several years with the maximum of eight. After dropping all observations that did not have sufficient data for calculating the cost function, the dataset included 882 MFIs with the average of about 3 years of data, or 2,712 total annual observations where output is measured by the number of clients. These observations represent 93 countries. The data cover the period 1998-2007.

Although the data are self-reported, most MFIs that disclosed the detailed data necessary for the calculation of a cost function are considered high quality with a MIXMARKET rating of three stars (78%), which marks that an MFI has at least two years of financial and outreach data reported or a rating of four stars (33%), which marks an MFI with audited financial statements. All values are in US dollars.

Total cost is the sum of financial and operating expenses. Salary is the ratio of operating expenses divided by the number of employees while financial costs are defined as the ratio of financial expenses to liability (this measure incorporates the cost of both loans and deposits measured at the actual price paid by the MFI). Financial depth is the ratio of the money aggregate including currency, deposits, and electronic currency (M3) over GDP and measures the level of financial development. Rural population is the proportion of people living in rural areas in the country in which the MFI operates while population density is the number of people per square kilometer.

Given that the data were not directly available they were calculated using the methodology proposed by Hermes, Lensink and Meesters (2009). Therefore, it is expected that outliers are present and we provide an easily implementable empirical procedure to mitigate their effects on the analysis.

Summary statistics of the variables used in the scope estimation are listed in Table 1. # of Borrowers represents the number of active borowers and # of Savers the number of active savers. The average number of borrowers is 58,000 but the rage is huge - from 9 to over 6 million borrowers and up to 32 million savers. The average ratio of operating expense per staff member (salary) is $12,933 and ranges from just under two to more than $121,000 (see table 1 for more details).

[PLACE TABLE 1 APPROXIMATELY HERE]

Results

For the model discussed in the previous section we estimate a SPSCM cost function with two outputs and two input prices. Input prices are scaled by labor costs to produce a relative capital labor price. Total costs, # of loans and # of deposits are all scaled by 1,000,000 to stabilize the smooth coefficients during bandwidth selection. All results were computed using the np package (Hayfield and Racine 2008) in R (R Development Core Team 2008).

In addition to normalized input prices entering the unknown smooth coefficients, we also included the year in which the MFI was observed and its region, the type of operation the MFI falls under, the population density and proportion of rural population in the country where the MFI operates and the level of financial depth. This addresses recent concerns that in cross-country studies environmental factors affect MFI's operations (Armedariz and Szafarz 2009). Given our ability to smooth discrete variables (year, MFI type and region) we employ discrete kernels (see Li and Racine 2007) for these variables and standard Gaussian kernels for the remaining continuous variables.

Robust cross validation

In the process of estimating the bandwidths we noticed that the least squares cross validation (LSCV) criteria was extremely sensitive to the presence of outliers (see Leung 2005). To remedy this we used the suggestion of Henderson and Kumbhakar (2006, footnote 4) and removed outliers prior to estimating the bandwidths via LSCV.[5] These outliers were then used to estimate scope economies.

To determine outliers we tried several different approaches couched in terms of distance-based methods. The simplest approach is to create a robust version of the Mahalanobis distance:

$$RD_i = \sqrt{(x_i - \mu)' C^{-1} (x_i - \mu)},$$

where μ is a robust estimate of the mean of the data (used for smoothing) and C is a robustly estimated covariance matrix. The approach of Rousseeuw and van Driessen (1999) estimates C such that C has the smallest determinant and contains at least J points. J in this setting represents the robustness of the covariance matrix estimator. Alternatively, one could employ the recent outlier detection method of Filzmoser, Maronna and Warner (2008). A novel feature of this approach is that it uses principal component analysis which allows faster computation and provides better outlier detection in high dimensions. [6]

Roughly 10% of our estimates of scope economies were over 100% in magnitude. These estimates drastically affect the mean estimates and, in some cases, the upper and lower quartiles. Therefore, in this section, we present primarily our results obtained from the dataset excluding these extreme estimates. We note that our qualitative results are robust to whether these estimates are included or not.[7]

Scope Economies

Table 2 and figure 1 show the variation of scope economies by region. The tabulated results are the quartile and mean values for estimated scope economies as well as fixed and complementary cost components across regions whereas the figure provides the joint density of estimated scope economies and region using the significant set of estimates. The combined economies of scope appear to be the highest in the Middle East and in Eastern Europe and the lowest in Latin America and Africa.

[PLACE TABLE 2 and FIGURE 1 APPROXIMATELY HERE]

Table 3 and figure 2 provide a more in-depth analysis of how scope economies vary by MFI type.[8] The figure provides the joint density of estimated scope economies and MFI type using the significant set of estimates. While typically MFIs classified as non-profits and non-bank financial institutions do not offer savings/deposits, they seem to be the ones with the highest potential for realizing scope economies.

[PLACE TABLE 3 AND FIGURE 2 APPROXIMATELY HERE]

Of particular interest in this analysis is the relation of scope economies to the proportion of rural population in the country as there is substantial interest in offering savings in rural areas and scope economies may contribute to its feasibility. Joint density plots of estimated scope economies and rural population density (figures not shown due to space limitations) suggest that economies of scope are non-linear and peak for MFIs in countries with about 70-75 percent of rural population. Further decomposing the estimated joint densities by MFI type, we focus on Non-Profit and Non-Bank MFIs as these splits are the largest groups. We find that scope economies are higher for non-banks whereas, for non-profits, the landscape is more sensitive to changes in the rural population. However, this result should be interpreted with caution because, in comparison to banks, both non-banks and non-profits are usually under-represented in rural areas.

The general conclusion from further analysis is that environmental/external factors matter for scope economies which vary by geographical region and by population mix. When diseconomies of scope are present, savings comes with its own added cost. We find evidence of some diseconomies of scope present in non-profits (particularly in more urban countries). In Africa, the diseconomies increase with the share of rural population, whereas in Latin America and Asia the diseconomies transpire mostly in the more urban countries.

Scope Economies Components

For a better understanding of the nature of scope economies in microfinance, we look at its main components - the fixed cost and complementary costs scope economies - by both MFI type and region with respect to rural population densities. The results show where economies of scope are arising across a variety of strata as well as how they differ based on where and how the MFI is setup. This information is important for policy design aimed at improving MFI operations.

In table 4 the first block is for all of estimates whereas the second block is for our estimates which are deemed statistically significant when paired with their corresponding standard errors at the 1% level. While, on average, the scope economies are positive, there are some diseconomies that are much higher in the complementary cost component.

[PLACE TABLE 4 APPROXIMATELY HERE]

Density plots of scope economies by MFI type (not shown), as well as table 3, suggest that the scope economies are mostly due to fixed cost sharing and that non-profit, non-bank, and cooperative MFIs (in that order) possess highest scope economies due to fixed cost sharing. Figure 3 shows the relation between the nature of scope economies and rural population density in non-profits and non-bank MFIs.[9] Density shapes suggest that, for both non-bank financial institutions and non-profit MFIs, the fixed costs component becomes more important in countries with more rural population. The diseconomies of scope, when present, are the highest in the complementary cost component.

[PLACE FIGURE 3 APPROXIMATELY HERE]

Conclusions

While economies of scope of lending and mobilizing deposits in banking are justified theoretically (Diamond 1984) and found empirically (see Sounders 1999), in microfinance the existence and magnitude of scope economies has not been investigated. We use a semiparametric smooth coefficient model to estimate these economies using a dataset put together from MFIs with over 2700 annual observations from across the globe. This model affords the researcher sufficient flexibility in incorporating zero valued input prices and outputs into the cost function without resorting to *ad hoc* data replacement techniques.

We estimate a generalized cost function capable of producing meaningful estimates of scope economies that seamlessly incorporates environmental variables and decompose overall scope economies into fixed and complementary cost components. These components of scope economies are important because they provide direct evidence as to how MFIs could use alternative solutions to cut costs to produce both deposits and loans. Further, this paper also successfully employed robust cross validation methods which should prove useful in future nonparametric work outside of the application here. Moreover, we presented graphical evidence supporting the fact that MFIs may possess different degrees of scope economies based on location and rural population, all of which, when considered in concert suggest that policy recommendations for MFIs hinge on these factors to design and effective strategy for lowering costs.

Notes

[1]Given the appeal of this functional form in applied settings, various authors have dealt with the zero output (or zero input price) problem in a variety of ways. The simplest approach is to add a small number to all observations that have a zero output value (Berger and Humphrey 1991) or to introduce a Box-Cox transformation parameter to all outputs.

[2]We note that this model was also used to obtain estimates for scope economies of rated MFIs by Hartarska, Parmeter and Mersland (2009).

[3]We use the standard least squares cross validation (LSCV) selection method to obtain our bandwidths. This method has recently been shown to have desirable properties by Li and Racine (2009).

[4]Let $z_i = [z_i^d, z_i^c]$, where z_i^d is a vector of discrete regressors and z_i^c is a vector assuming continuous values. One can further decompose z_i^d into subvectors of ordered and unordered discrete regressors, z_i^{do} and z_i^{du}, respectively.

[5]Henderson and Kumbhakar (2006) only mentioned, but did not actually report their results from, this approach in their work so this marks the first reported application of this insight on a form of robust cross-validation.

[6]Both of the methods described here, as well as others, can be accessed in R via the packages "mvoutlier" (Gschwandtner and Filzmoser 2009) and "robustbase" (Maechler 2009).

[7]Results including these extreme estimates are available upon request.

[8]Rural banks classification is only for MFIs in Indonesia while banks serving predominantly rural clients are not classified as rural banks by the MIXMARKET in other countries. The category Other (MFIs without a category assigned to them by MIXMARKET) is less than one percent. These two categories represent less than 5 percent of the sample and are excluded from the analysis.

[9]The densities were constructed using the Gaussian kernel and rule-of-thumb bandwidths.

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Table 1: **Summary Statistics For MFI Data.**

Variable	Mean	Std. Dev.	Min	Median	Max
# Borrowers	61701.959	353893.455	9	8529.5	6397635
# of Savers	111617.414	1505987.318	0	0	32252741
Total Cost	5651212.031	35749638.418	0	908590.160	835000000
Financial Costs	0.098	0.167	0	0.062	2.72
Salary	12933.108	10581.880	1.784	10879.459	121204.09
Financial Depth	0.418	0.257	0.070	0.372	2.34
Pop. Density	130.710	196.875	2	64	1109
Rural Pop.	51.594	19.824	6.6	50.020	87.98
MFI Type					
Bank	0.067	–	0	–	1
Cooperative	0.176	–	0	–	1
Non-Bank	0.328	–	0	–	1
Non-Profit	0.378	–	0	–	1
Rural	0.034	–	0	–	1
Other	0.018	–	0	–	1

Table 2: **Quartile And Mean Estimates of Scope Economies And Its Components By Region.**

	$Q1$	$Q2$	$Q3$	Mean	$Q1$	$Q2$	$Q3$	Mean
			Africa				Latin America	
$SCOPE$	0.009	0.228	0.529	0.245	−0.098	0.013	0.290	0.105
	(0.194)	(0.223)	(0.131)	(0.100)	(0.201)	(0.359)	(8.276)	(32.917)
$SCOPE_{FC}$	−0.003	0.182	0.514	7.380	−0.190	−0.021	0.175	−0.039
	(0.241)	(0.156)	(0.174)	(2.182)	(11.410)	(0.187)	(0.105)	(0.434)
$SCOPE_{CC}$	−0.228	0.008	0.125	−6.380	−0.013	0.034	0.165	0.144
	(0.077)	(0.045)	(0.055)	(2.182)	(0.167)	(0.036)	(128.634)	(2.613)
			Asia				Middle East	
$SCOPE$	−0.009	0.294	0.711	0.327	0.236	0.861	0.999	0.638
	(0.026)	(3.309)	(0.501)	(5.945)	(0.281)	(0.065)	(0.000)	(0.038)
$SCOPE_{FC}$	0.084	0.411	0.947	1.279	0.189	0.525	0.971	0.536
	(0.068)	(0.113)	(0.177)	(2.538)	(2.483)	(0.174)	(0.045)	(0.139)
$SCOPE_{CC}$	−0.528	−0.095	0.055	−0.943	−0.047	0.011	0.094	0.092
	(1.760)	(2.265)	(3.413)	(4.163)	(0.040)	(0.030)	(0.025)	(0.044)
			Eastern Europe					
$SCOPE$	0.071	0.365	0.759	0.384				
	(0.155)	(0.174)	(0.701)	(0.094)				
$SCOPE_{FC}$	0.095	0.370	0.747	0.501				
	(0.137)	(2.884)	(1.152)	(0.665)				
$SCOPE_{CC}$	−0.076	0.011	0.066	−0.115				
	(0.051)	(0.134)	(1.149)	(0.579)				

Figure 1: **Joint Density Of Estimated Scope Economies And Region.**

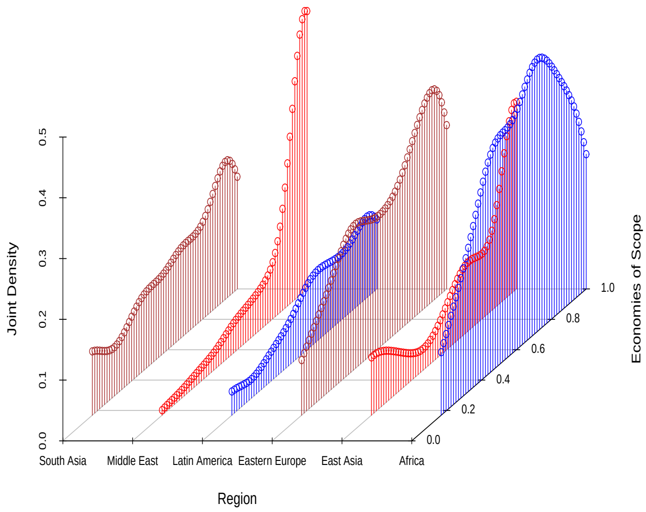


Figure 2: **Joint Density Of Estimated Scope Economies And MFI Type.**

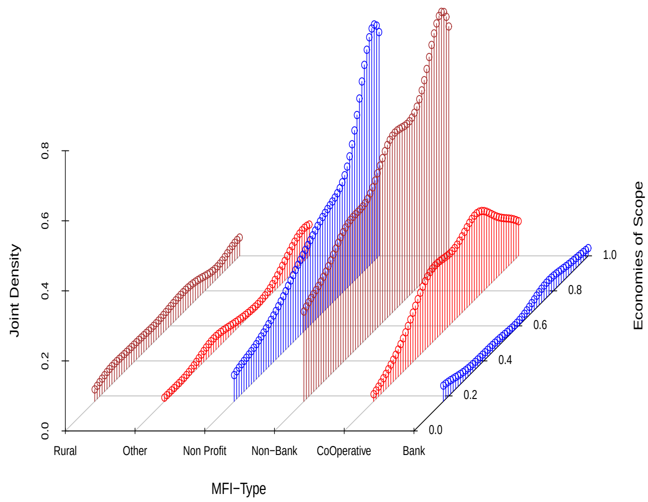


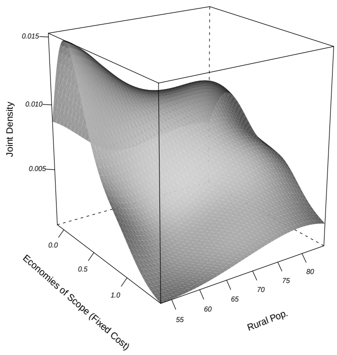
Table 3: **Quartile And Mean Estimates Of Scope Economies And Its Components By MFI Type.**

	$Q1$	$Q2$	$Q3$	Mean	$Q1$	$Q2$	$Q3$	Mean
	Bank				Non-Profit			
$SCOPE$	−0.128	0.020	0.227	0.061	−0.060	0.148	0.633	0.236
	(0.059)	(0.087)	(0.188)	(0.078)	(1.991)	(2.634)	(0.207)	(14.379)
$SCOPE_{FC}$	−0.017	0.040	0.141	0.092	−0.104	0.124	0.565	0.500
	(0.025)	(0.114)	(0.091)	(0.516)	(0.320)	(3.346)	(0.179)	(0.198)
$SCOPE_{CC}$	−0.105	0.001	0.069	−0.035	−0.123	0.032	0.203	−0.258
	(0.228)	(0.046)	(0.046)	(0.270)	(0.120)	(0.016)	(0.209)	(0.083)
	Cooperative				Non-Bank			
$SCOPE$	−0.039	0.181	0.553	0.228	0.015	0.250	0.658	0.324
	(0.220)	(0.175)	(0.080)	(0.360)	(0.203)	(3.787)	(0.915)	(0.411)
$SCOPE_{FC}$	−0.023	0.189	0.547	0.327	0.010	0.281	0.725	0.460
	(0.425)	(0.324)	(0.622)	(0.128)	(0.126)	(0.385)	(0.055)	(8.089)
$SCOPE_{CC}$	−0.069	0.039	0.136	−0.101	−0.128	−0.010	0.036	−0.136
	(0.189)	(0.125)	(0.143)	(0.146)	(2.294)	(0.025)	(0.025)	(0.833)

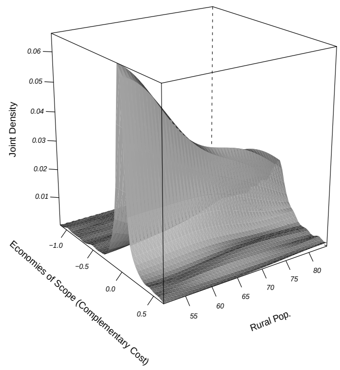
Table 4: **Quartile And Mean Estimates Of Scope Economies And Its Components.**

	All Estimates				Statistically Significant Estimates			
	$Q1$	$Q2$	$Q3$	Mean	$Q1$	$Q2$	$Q3$	Mean
$SCOPE$	-0.025	0.193	0.606	0.264	0.479	0.726	0.947	0.687
	(0.081)	(0.093)	(0.196)	(0.270)	(0.091)	(0.041)	(0.034)	(0.028)
$SCOPE_{FC}$	-0.023	0.180	0.618	5.304	0.347	0.682	1.020	16.610
	(0.197)	(0.151)	(7.357)	(0.235)	(0.112)	(0.099)	(0.127)	(3.421)
$SCOPE_{CC}$	-0.119	0.007	0.113	-5.004	-0.208	0.011	0.163	-15.703
	(0.424)	(0.013)	(1.031)	(1.503)	(0.316)	(0.019)	(0.613)	(3.439)

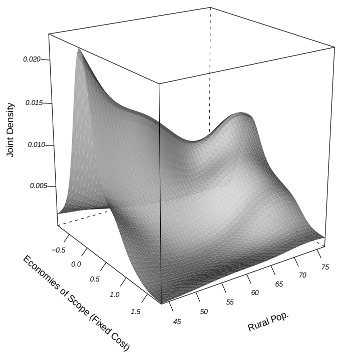
Figure 3: **Joint Density Of Estimated Scope Economies Components And Rural Population By Type.**



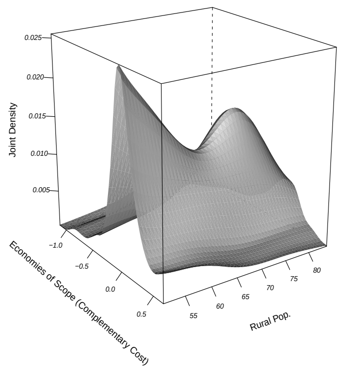
(a) Non-Banks, Fixed Costs



(b) Non-Banks, Complementary Costs



(c) Non-Profits, Fixed Costs



(d) Non-Profits, Complementary Costs